Deep Learning: Homework 1

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Google Colab Link: https://colab.research.google.com/drive/18foX8skV_cUcMrFoC9OKSEHc-5xmXwmf?usp=sharing

Libraries

```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sb
```

Part 1

(1) Import the iris flowers dataset using pandas.read_csv() with the following URL link (10pt); The DataFrame must have the following column names: `sepal length (cm)`, `sepal width (cm)`, `petal length (cm)`, `petal width (cm)`, and `class`; (5pt) Print the first 5 rows of the DataFrame (5pt).

```
data = pd.read_csv("http://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.data",
                   names=['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal width (cm)','class'])

iris_df = pd.DataFrame(data)

iris_df.head()
```

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	class
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa

(2) Summarize the dataset

- Print out a concise summary of the DataFrame using .info() and the shape of the DataFrame (5 pt)

```
print(iris_df.info())
print("\n\nShape:", iris_df.shape)
print("\n\n Shape:", iris_df.shape)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   sepal length (cm)  150 non-null    float64
 1   sepal width (cm)   150 non-null    float64
 2   petal length (cm)  150 non-null    float64
 3   petal width (cm)   150 non-null    float64
 4   class              150 non-null    object 
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
None


 Shape: (150, 5)
```

- Print out the statistics of the continuous columns using .describe() (i.e., the four attribute columns) (5 pt)

```
print(iris_df[0:3].describe())
```

```
       sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)
count                3.0          3.000000           3.000000      3.000000e+00
mean                 4.9          3.233333           1.366667      2.000000e-01
std                  0.2          0.251661           0.057735      3.399350e-17
min                  4.7          3.000000           1.300000      2.000000e-01
25%                  4.8          3.100000           1.350000      2.000000e-01
50%                  4.9          3.200000           1.400000      2.000000e-01
75%                  5.0          3.350000           1.400000      2.000000e-01
max                  5.1          3.500000           1.400000      2.000000e-01
```

- Print out the number of rows that belong to each class (5 pt)

```
iris_pivot = pd.pivot_table(iris_df, values = "sepal length (cm)", index = "class", aggfunc = len, margins = True)
iris_pivot.columns = ['# of Rows']
iris_pivot
```

	# of Rows
class	
Iris-setosa	50.0
Iris-versicolor	50.0
Iris-virginica	50.0
All	150.0

(3) Data Visualization

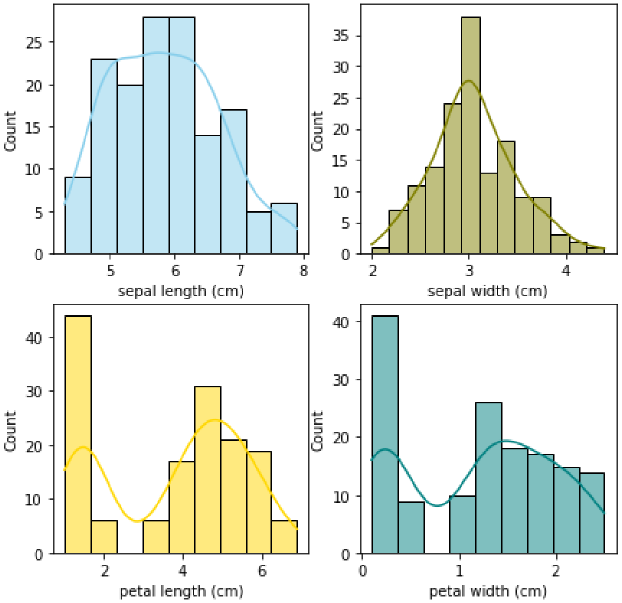
- Separate out the first four columns of the original DataFrame into a new DataFrame and print out the first 5 rows of the new DataFrame (5

```
iris_subset = iris_df[['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal width (cm)']]
iris_subset.head()
```

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2

- Univariate Plots: plot a histogram for each column of the new DataFrame (5 pt)

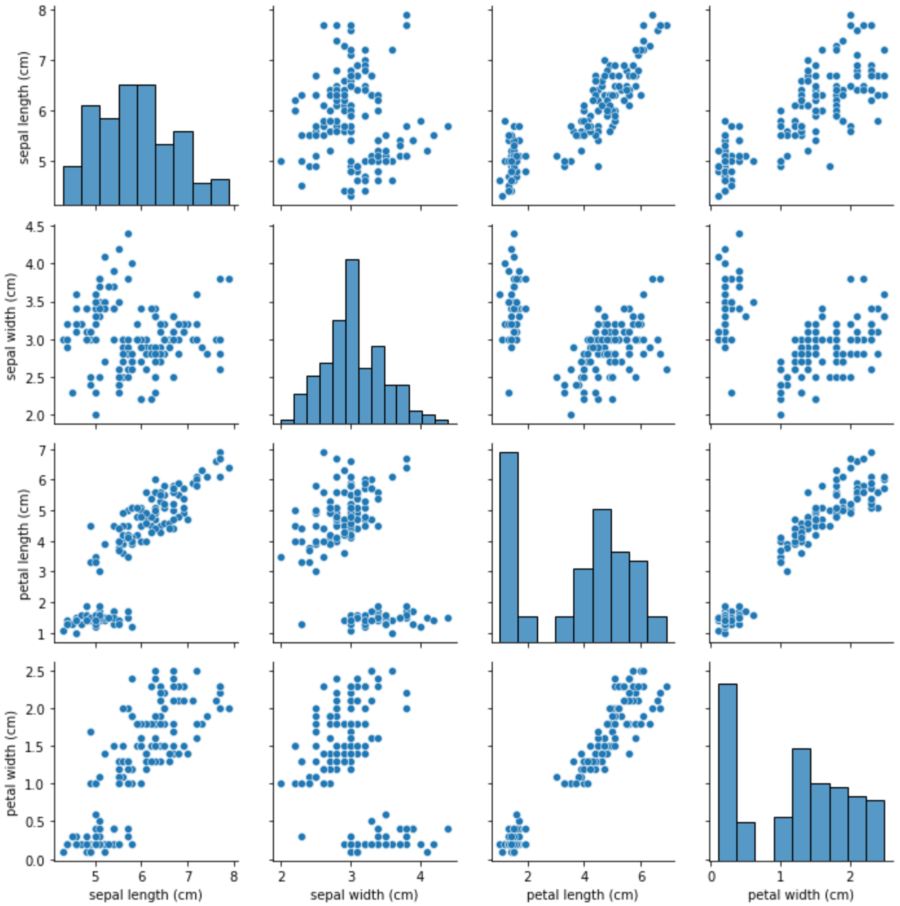
```
fig, axs = plt.subplots(2, 2, figsize=(7, 7))

sb.histplot(iris_subset, x="sepal length (cm)", kde=True, color="skyblue", ax=axs[0, 0])
sb.histplot(iris_subset, x="sepal width (cm)", kde=True, color="olive", ax=axs[0, 1])
sb.histplot(iris_subset, x="petal length (cm)", kde=True, color="gold", ax=axs[1, 0])
sb.histplot(iris_subset, x="petal width (cm)", kde=True, color="teal", ax=axs[1, 1])

plt.show()
```



- Multivariate Plots: plot a scatter plot for each pair of the columns of the new DataFrame using the pandas.plotting.scatter_matrix function (5 pt)

```
multi_plot = sb.PairGrid(iris_subset)
multi_plot.map_diag(sb.histplot)
multi_plot.map_offdiag(sb.scatterplot)
```

```
<seaborn.axisgrid.PairGrid at 0x7f23b4ee9890>
```



Part 2

(1) Import the `Census Income (Adult)` dataset using Pandas, use the 14 attribute names (i.e., `age`, `workclass`, ..., `native-country`) as explained in the dataset description as the first 14 column names and `salary` as the last column name (5 pt) , view the strings ‘?’, ‘ ?’, ‘? ’, or ‘

? ’ as the missing values and replace them with NaN (the default missing value marker in Pandas) (10 pt), and print out the first five rows of the DataFrame. (5 pt)

```
census_data = pd.read_csv("http://archive.ics.uci.edu/ml/machine-learning-databases/adult/adult.data",
                          names = ['age', 'workclass', 'fnlwgt', 'education', 'education-num', 'marital-status',
                                   'occupation', 'relationship', 'race', 'sex', 'capital-gain', 'capital-loss',
                                   'hours-per-week', 'native-country', 'salary'],
                          index_col = False)

missing_values = ['?', ' ?', '? ', ' ? ']

census_df = census_data.replace(missing_values, np.nan)
census_df.head()
```

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	rela
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	N
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	N
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	
4	28	Private	338409	Bachelors	13	Married-	Prof-specialty	

(2) Dataset checking and cleaning

- Print out a concise summary of the DataFrame and observe if null values exist in each column of the DataFrame by checking the summary (10 pt)

```
census_df.isnull().sum()
```

```
age                  0
workclass         1836
fnlwgt               0
education            0
education-num        0
marital-status       0
occupation        1843
relationship         0
race                 0
sex                  0
capital-gain         0
capital-loss         0
hours-per-week       0
native-country     583
```

```
    salary               0
    dtype: int64
```

- Filter out the rows that contain missing values and print them out (10 pt)

```
null_rows = census_df[census_df.isna().any(axis=1)]
print(null_rows)
```

```
           age workclass  fnlwgt  ... hours-per-week  native-country  salary
    14      40   Private  121772  ...             40             NaN    >50K
    27      54       NaN  180211  ...             60           South    >50K
    38      31   Private   84154  ...             38             NaN    >50K
    51      18   Private  226956  ...             30             NaN   <=50K
    61      32       NaN  293936  ...             40             NaN   <=50K
    ...    ...       ...     ...  ...            ...             ...     ...
    32530   35       NaN  320084  ...             55   United-States    >50K
    32531   30       NaN   33811  ...             99   United-States   <=50K
    32539   71       NaN  287372  ...             10   United-States    >50K
    32541   41       NaN  202822  ...             32   United-States   <=50K
    32542   72       NaN  129912  ...             25   United-States   <=50K

    [2399 rows x 15 columns]
```

- Drop the rows of the DataFrame with missing values using .dropna() and observe if null values still exist in each column by checking the concise summary again (10 pt)

```
census_new = census_df.dropna(axis=1)
census_new.isnull().sum()
```

```
    age               0
    fnlwgt            0
    education         0
    education-num     0
    marital-status    0
    relationship      0
    race              0
    sex               0
    capital-gain      0
    capital-loss      0
    hours-per-week    0
    salary            0
    dtype: int64
```